On the Determinants of Currency Crises: The Role of Model Uncertainty

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In this contribution, we tackle explicitly the issue of model uncertainty in the framework of binary variable models of currency crises. Using Bayesian model averaging techniques, we assess the robustness of the explanatory variables proposed in the recent literature for both static and dynamic models. Our results indicate that the variables belonging to the set of macroeconomic fundamentals proposed by the literature are very fragile determinants of the occurrence of currency crises.

1 Introduction

The vast majority of the empirical literature uses limited dependent variable – logit or probit – models to assess the effect various potential determinants have on the probability of a currency crisis. The discrete crisis variable (crisis versus non-crisis observation) is regressed on a set of fundamental indicators, e.g. current account and government balances, exchange rate overvaluation or liquidity ratios. The choice of regressors is typically inspired by the three generations of theoretical models on balance of payment crises. In one of the most recent contributions on this topic, Bussière (2007) overhauls the usually static specification, in which, moreover, all regressors tend to enter at the same lag. He extends the usual set of explanatory variables by including several lags of the regressors as well as of the dependent binary crisis variable. He finds that there are several variables that significantly affect the probability of a crisis in a dynamic logit model. However, the impact of the indicators ranges between the short run (4–6 months, e.g. for liquidity measures) and the very long run (2 years, e.g. in case of an overappreciation of the exchange rate). In addition, his results indicate that past crisis episodes increase the probability of a new attack, particularly in the short run.

Notwithstanding substantial variations in the literature on early warning systems for currency crises with respect to methodology, data as well as results, there is one general caveat which applies to all existing binary choice models. Given that there is no unique theoretical framework that links the potential set of determinants with the actual occurrence of currency crises, the issue of model uncertainty surrounding both the choice of variables and the estimates obtained deserves to be treated seriously. Model uncertainty can be explicitly taken into account by means of Bayesian statistical techniques, in particular the Bayesian model averaging (BMA) methodology. It proposes averaging the parameter values over all (relevant) alternative models, using posterior model probabilities as the respective weights to evaluate the relative importance of different variables (see Raftery, 1995, for a general discussion and Sala-i-Martin, Doppelhofer and Miller, 2004, Fernández, Ley and Steel, 2001, or Crespo Cuaresma and Doppelhofer, 2007, for applications to economic growth regressions).

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Given that different theoretical settings are used to explain different crisis episodes, the various authors employ alternative sets of potential explanatory variables (with intersections that are not necessarily empty) to assess the probability of a crisis occurring. The *first-generation* models (e.g. Krugman, 1979, Flood and Garber, 1984) concentrate on bad economic policy leading to unsustainable developments of some fundamental macroeconomic variables. The fixed exchange rate regime is then abandoned as the central bank's foreign reserves are eventually exhausted. The *second generation* of currency crisis models (e.g. Obstfeld, 1994) explains crises as the consequence of self-fulfilling expectations in theoretical settings with multiple equilibria. By contrast, the *third generation* of models (e.g. Krugman, 1998) assumes that the outbreak of a currency run is a symptom of accumulated problems in the banking and financial sectors. In the theoretical setting, government guarantees aimed at attracting foreign investment lead to a bubble on the asset market that eventually bursts and creates the crisis. Obviously, given the differences in the theories regarding the ultimate cause of the currency crises in the different model generations, the potential empirical determinants to be included in econometric studies vary strongly depending on the theory used to select covariates.

The objective of the present paper is to revisit binary variable models for currency crises based on macroeconomic fundamental data by explicitly taking into account model uncertainty. In particular, we want to work out to what extent model uncertainty undermines the robustness of the explanatory variables of the logit models championed in the literature (e.g. Bussière and Fratzscher, 2006, or Bussière, 2007). Our results indicate that the macroeconomic variables usually used in empirical studies of currency crises are very fragile determinants of the occurrence of such episodes.

The remainder of the paper is structured as follows: Section 2 sketches the Bayesian model averaging procedure. In section 3, we describe the data and define the variables. Section 4 presents the results on the extent to which model uncertainty matters, while section 5 concludes.

2 Dealing with Model Uncertainty: Bayesian Model Averaging

The binary variable we are interested in modeling takes value 1 if a currency crisis occurs in period t $(y_i = 1)$ and 0 if no currency crisis is observed $(y_i = 0)$. A stereotypical regression aimed at assessing the effect of a set of variables $\{\mathbf{x}_j\}_{j=1}^{K}$ on the probability of a currency crisis occurring is given by

$$\mathrm{P}(y_i = 1 \mid \{\mathbf{x}_j\}_{j=1}^{K}) = F(\mathbf{X}_K^{'}\beta), \qquad (1)$$

where $F(z)$ will typically be a logistic function $(F(z) = (1+e^{z})^{-1}$ (for the logit model) or the distribution function of a normal random variable $F(z) = \Phi(z)$ (for the probit model)), $\mathbf{X}_K = (x_1 \ldots x_K)$, which is a subset of $\mathbf{X}_{\overline{K}} = (x_1 \ldots x_{\overline{K}})'$, contains all possible regressors ($\overline{K}$ of them), and $\beta = (\beta_1 \ldots \beta_K)'$. In principle, many candidate variables can be proposed as potential covariates in (1).

So far, the literature has tended to concentrate on an arguably tiny subset of this model space. We will use model averaging techniques (i.e. average over all these alternative models) using Bayes factors so as to evaluate the relative importance of the different variables as determinants of a currency crisis. In a setting with M competing models, $\{M_1,\ldots,M_M\}$, which are defined by the choice of independent variables, so that $M = 2^{\bar{K}}$, Bayesian inference about a single parameter of interest, β_i, is based on its posterior distribution (that is, the distribution given the data, $\mathbf{Y} = \{y\mathbf{X}_K\}$),

$$\mathrm{P}(\beta_i \mid \mathbf{Y}) = \sum_{m=1}^{M} \mathrm{P}(\beta_i \mid \mathbf{Y}, M_m)\mathrm{P}(M_m \mid \mathbf{Y}), \tag{2}$$

where the posterior probabilities $\mathrm{P}(M_k \mid \mathbf{Y})$ are given by

$$\mathrm{P}(M_k \mid \mathbf{Y}) = \frac{\mathrm{P}(\mathbf{Y} \mid M_k)\mathrm{P}(M_k)}{\sum_{m=1}^{M} \mathrm{P}(\mathbf{Y} \mid M_m)\mathrm{P}(M_m)}. \tag{3}$$

The posterior model probabilities can thus be obtained as the normalized product of the integrated likelihood for each model ($\mathrm{P}(\mathbf{Y} \mid M_k)$) and the prior probability of the model ($\mathrm{P}(M_k)$). Note that for the simple case $m = 2$ the posterior odds for one model against the other can be readily written as the product of the Bayes factor and the prior odds. Further assuming equal priors across models, the posterior odds are equal to the Bayes factor ($\mathrm{P}(\mathbf{Y} \mid M_2)/\mathrm{P}(\mathbf{Y} \mid M_1)$). The Bayes factor, in turn, can be accurately approximated (see Leamer, 1978, and Schwarz, 1978) as

$$\frac{\mathrm{P}(\mathbf{Y} \mid M_2)}{\mathrm{P}(\mathbf{Y} \mid M_1)} = N^{(k_1-k_2)/2}\left(\frac{Lik_2}{Lik_1}\right), \tag{4}$$

where N is the number of observations, k_j and Lik_j are, respectively, the number of parameters and the likelihood of model j. This simple approximation allows us to compute (3) and the corresponding statistics based on (3).

This implies that for a given prior on the model space, the posterior distribution of β can be obtained as a weighted average of the model-specific estimates weighted by the posterior probability of the respective models. If the cardinality of the model space is computationally tractable, (3) can be obtained directly and (2) can be computed. In particular, the expected values of β and its variance, $\mathrm{E}(\beta \mid \mathbf{Y})$ and $\mathrm{var}(\beta \mid \mathbf{Y})$, respectively, can be computed as follows:

$$\begin{aligned} \mathrm{E}(\beta_i \mid \mathbf{Y}) &= \sum_{m=1}^{M} \mathrm{E}(\beta_i \mid \mathbf{Y}, M_m)\mathrm{P}(M_m \mid \mathbf{Y}), \\ \mathrm{var}(\beta_i \mid \mathbf{Y}) &= \sum_{m=1}^{M} [\mathrm{var}(\beta_i \mid \mathbf{Y}, M_m) + \mathrm{E}(\beta_i \mid \mathbf{Y}, M_m)^2]\mathrm{P}(M_m \mid \mathbf{Y}) - \mathrm{E}(\beta_i \mid \mathbf{Y})^2. \end{aligned} \tag{5}$$

The posterior mean and variance can be used to make inference about the quantitative effect that changes in the covariates have on the probability of a currency crisis, while model uncertainty is explicitly taken into account. Several methods have been proposed for approximating the expression in (3) when the cardinality of the model space makes the problem intractable. The *leaps and bounds* algorithm, the Markov chain and Monte Carlo Model Composite (MC^3) or Occam's window are possible methods of limiting the number of models to be evaluated when computing (3) (see Raftery, 1995, for an excellent description of these methods).

In our empirical application we will use a simple MC[3] algorithm to evaluate the posterior distribution based on the work of Madigan and York (1995), which was also used recently by Fernández, Ley and Steel (2001) in the framework of cross-country growth regressions.[3] This Markov chain Monte Carlo method implements the random walk chain Metropolis-Hastings algorithm in the model space as follows. In a given replication $r-1$ of the algorithm, a candidate model M^r is proposed, which is randomly drawn from the group of models composed by the model active in that replication (M^{r-1}), the same model with an extra variable added to the specification and the same model with a variable removed. The proposed model is accepted with a probability given by

$$\alpha(M^{s-1}, M^s) = \min\left[\frac{\mathrm{P}(\mathbf{Y} \mid M^s)\mathrm{P}(M^s)}{\mathrm{P}(\mathbf{Y} \mid M^{s-1})\mathrm{P}(M^{s-1})}, 1\right], \tag{6}$$

which is just the Bayes factor comparing M^{s-1} and M^s if equal prior probability is assumed across models, so that $\mathrm{P}(M^{s-1})$ and $\mathrm{P}(M^s)$ cancel out in the expression above. This algorithm is repeated a large number of times, and the sums defined above are computed for the group of models replicated, which will tend to cover model subspaces with the highest posterior probability.

In the same fashion, posterior inclusion probabilities for the different variables can be obtained by summing the posterior probability of models containing each variable. This measure thus captures the relative importance of the different covariates as determinants of a currency crisis and can be interpreted as the probability that a given variable belongs to the true specification.

3 Data and Variable Descriptions

The early warning system for currency crises we present in this paper is derived from a binary variable model based on macroeconomic fundamental data, in the spirit of the classical contributions by e.g. Frankel and Rose (1996). Since currency crises are rare events, it is necessary in this type of model to pool country/time data in order to increase the number of observations and obtain sufficient degrees of freedom. Naturally, this procedure implicitly imposes the assumption of parameter homogeneity across countries and in the time dimension. The resulting first requirement on our sample thus was that the crisis episodes considered be sufficiently homogeneous, that is, characterized by a similar development of fundamentals. In addition, however, it was also desirable in this context to employ the same data source as a recent benchmark study that uses a "standard" binary variable approach (that is, without explicitly dealing with model uncertainty) so as to determine the value added by model averaging.

For these reasons, we decided to use as a yardstick for comparison the dataset of one of the most recent papers on this issue by Bussière (2007), who exercised great care in constructing a sample that is sufficiently homogeneous

[3] *Koop (2003) also describes this method thoroughly.*

to ensure that a common development of fundamentals driving the crises may be expected. Against this backdrop, the overall sample consists of a pool of observations on 27 countries recorded from January 1994 to March 2003 and contains approximately 1,400 observations.[4] Observations prior to 1994 are taken out of the sample to avoid biases emanating from hyperinflationary experiences in Latin American countries and the early years of transition toward a market economy in Central and Eastern European economies.[5]

The dependent binary variable is defined to equal 1 if a crisis occurs and 0 otherwise. Although in the common understanding a currency crisis might be associated predominantly with a dramatic devaluation of the exchange rate, the literature on early warning mechanisms usually tends to employ a broader definition of currency distress, using the concept of exchange market pressure. The latter is not uniformly defined in the literature, but it is usually the weighted average of some combination of changes in the real or nominal exchange rate, the country's foreign reserves and the real interest rate. The dependent variable is thus computed in two steps. First, the exchange market pressure index ($EMPI_{i,t}$) for country i at time t is defined as

$$EMPI_{i,t} = \omega_{RER}\left(\frac{\Delta RER_{i,t}}{RER_{i,t-1}}\right) + \omega_r\left(\Delta r_{i,t}\right) - \omega_{res}\left(\frac{\Delta res_{i,t}}{res_{i,t-1}}\right),$$

where RER stands for the real effective exchange rate, r is the short-term real interest rate and res the level of international reserves. In the next step, this continuous variable is transformed into a binary index which equals 1 whenever $EMPI_{i,t}$ exceeds the threshold of the country-specific mean ($\overline{EMPI}_i$) plus twice its standard deviation σ_{EMPI_i}:

$$CI_{i,t} = \begin{cases} 1 & if EMPI_{i,t} > \overline{EMPI}^i + 2\sigma_{EMPI_i}, \\ 0 & otherwise. \end{cases}$$

The choice of the explanatory right-hand side variables in (1) is motivated by the theoretical literature on currency crises on the one hand, and by the results of the existing empirical early warning models on the other. Table 1 lists the complete final set of variables, of which different combinations and transformations are used in the estimations below. Further details on the construction of the variables and the intuition behind their choice can be found in Bussière (2007).

The exchange rate variable is supposed to capture any excessive real overvaluation of the currency, which would be expected to increase the risk of devaluation. It is defined as the deviation of the real exchange rate from a

[4] *The countries included in the sample are Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Venezuela, China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, Thailand, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia, Slovakia, Slovenia, Turkey.*

[5] *Bussière and Fratzscher (2006) tested for slope homogeneity in a very similar dataset by comparing out-of-sample forecasts based on the parameter homogeneity assumption. From the good forecasting performance they conclude that the same parameter vector is suitable for different countries and episodes. In contrast, the sample used by Peltonen (2006), which contains also data on crises from the 1980s, suggests significant differences between Latin America and Asia.*

Table 1

Definition of Basic Variables

Variable name	Definition	Details
Exchange rate, deviation from trend	$REERDEV_{i,t} = \frac{REER_{i,t} - Trend_{i,t}}{Trend_{i,t}} * 100$	Trend defined as a simple linear trend
Lending boom	$LB_{i,t} = \left(\frac{CPS_{i,t}}{GDP_{i,t}} - \frac{\overline{CPS}_{i,t-24}}{GDP_{i,t-24}} \right) * 100$	$\frac{\overline{CPS}_{i,t-24}}{GDP_{i,t-24}} = \frac{1}{12} \sum_{k=0}^{11} \frac{CPS_{i,t-24-k}}{GDP_{i,t-24-k}} * 100$ $CPS_{i,t}$ = credit to the private sector
Short-term debt/reserves	$STDR_{i,t} = \frac{STD_{i,t}}{RES_{i,t}} * 100$	$STD_{i,t}$ = short-term debt $RES_{i,t}$ = international reserves
Total debt/reserves	Analogous to short-term debt/reserves	Locational or consolidated definition
Current account balance	$\frac{CA_{i,t}}{GDP_{i,t}}$	
Government balance	$\frac{GB_{i,t}}{GDP_{i,t}}$	
Financial contagion	$CONT_{i,t} = \sum_{j=1}^{N-1} EMPI_{i,t} * Correl_{i,j}$	$Correl_{i,j}$ = correlation of equity market returns
Datastream index, total market	12-month percentage change	Broad index
Datastream index, banks	12-month percentage change	Subindex
Datastream index, financial institutions	12-month percentage change	Subindex
GDP growth rate	Annual growth rate of GDP	

Source: Authors' compilation based on Bussière (2007).

linear trend. Since data on nonperforming loans are barely available because of underreporting, the lending boom indicator is meant to serve as a proxy. It is defined as the deviation of credit to the private sector (CPS_t^i) from a one-year average with a two-year lag. The ratio of short-term debt to reserves (and analogously the total debt indicator) reflects the Greenspan-Guidotti rule, which states that reserves should cover entirely the amount of external debt that investors can sell in the short term in case of an attack. A rise of this indicator, which reflects either a rise in debt or a fall of reserves, should render a crisis more likely. The total debt indicator is defined analogously for two different definitions: the locational (lc) and the consolidated concept (cc).[6] The set of explanatory variables further contains the current account and government surpluses, both normalized with the respective country's GDP. The sign of these two indicators is expected to be negative – the higher the surplus (the lower the deficit), the lower should be the probability of an attack. Bussière and Fratzscher (2006) show that contagion across countries is only significant via the financial and not via the trade channel, so only the former was taken into account in Bussière (2007). Financial interlinkages of a country i with all other countries in the sample are modeled as the average of the other

[6] *The locational banking statistics gather data on international financial claims and liabilities of bank offices resident in the reporting countries on a gross (unconsolidated) basis, including those vis-à-vis own affiliates. In contrast, the consolidated concept covers claims reported by domestic bank head offices, including the exposures of their foreign affiliates, and are collected on a worldwide consolidated basis with inter-office positions being netted out. For details see Bank for International Settlements (2003).*

countries' $EMPI_t^j$ ($j = 1$ to $N-1$, $j \neq i$) weighted by the correlation of equity market returns in country i and country j. Intuitively, the parameter attached to this variable should show up positive in the estimation results. The three subsequent Datastream indices (a broad market index and two subindices on banks and financial institutions) account for the predictive power of financial markets. They are defined as a 12-month percentage change of each stock index and are expected to enter with a negative coefficient. Finally, year-on-year GDP growth is included, as higher economic growth should reduce the government's temptation to devalue its currency, e.g. in order to gain competitiveness.

4 Empirical Results: How Much Does Model Uncertainty Matter?

Following Bussière (2007), we will present results based on three types of specification. First, we deal with a purely static model, where lags of the dependent variable do not appear as extra regressors in the model, although all explanatory variables are evaluated with a one-month lag with respect to the crisis variable. We then address dynamic models, which on top of the exogenous set of variables employed in the static model also includes up to 6 lags of the crisis index as explanatory variables. Finally, the most general specification includes up to 24 lags of 6 selected variables

$(REERDEV, LB, STDR, \frac{CA}{GDP}, CONT, GROWTH)$.[7]

In table 2 we report the results of the BMA exercise for the static case, where all specifications in the model space have been evaluated in order to compute posterior inclusion probabilities and posterior expected values of the parameters.[8] We also deal explicitly with the issue of potential multicollinearity among the regressors. The second and third columns of the table present the posterior expected parameter values for each variable (second column) and the posterior inclusion probabilities (third column) for the BMA exercise, using all variables listed in table 1. The results of the BMA exercise are presented under "Static uncorrelated," after taking out variables whose correlation with some other explanatory variable was equal to or greater than 0.5 (both total debt indicators and one of the Datastream indices).

The posterior expected values of the parameters can be compared with the results obtained by Bussière (2007), which are reported in the sixth column for the simple static model and in the seventh column for the static model with fixed effects. Since Bussière alternates the set of included variables to avoid multicollinearity we report here the range in which his (significant) estimates fall (*n.s.* stands for nonsignificant, if no estimate on at least the 10% level was available). Two facts are especially noteworthy when considering the results in

[7] *Bussière (2007) also estimates models with fixed effects. He reports that the hypothesis that all country-fixed effects are equal to 0 can be rejected, but admits that the p-value of the test is close to 10%. He also estimated conditional logit models for both the static and the dynamic models. The results are very close to those obtained with the model where no fixed effects were used.*

[8] *In order to keep the table readable, we do not report the posterior variances of the parameters, which are available from the authors upon request.*

Table 2

BMA Results – Static Model

Variable	Static		Static uncorrelated		Bussière (2007) static	
	$E(\beta_i \mid Y)$	Inclusion prob.	$E(\beta_i \mid Y)$	Inclusion prob.	Simple static	Fixed effects
Exchange rate, deviation from trend	0.022487	0.001550	0.021211	0.001445	[0.025;0.042]	[0.032;0.045]
Lending boom	0.008857	0.002301	0.008854	0.002312	[0.006]	[0.005;006]
Short-term debt/reserves	0.000974	0.001280	0.000976	0.001278	[0.003;0.004]	[0.007;0.009]
Total debt/reserves (lc)	0.000542	0.001221			[0.002]	[0.004]
Total debt/reserves (cc)	0.000692	0.001581			[0.003]	[0.006]
Current account balance	−0.032851	0.001479	−0.032725	0.001473	n.s.	[−0.141;−0.077]
Government balance	0.048337	0.000942	0.048560	0.000945	[0.082]	n.s.
Financial contagion	0.051736	0.009448	0.051947	0.009797	[0.043]	[−0.015;0.043]
Datastream index, total market	−0.012897	0.031533	−0.012907	0.033148	n.s.	[−0.008]
Datastream index, banks	−0.010366	0.050357			n.s.	[−0.014]
Datastream index, financial institutions	−0.011919	0.090347	−0.011913	0.095018	n.s.	[−0.015]
Growth rate	−0.012887	0.000834	−0.014045	0.000838	[−0.052]	n.s.

Source: Authors' calculations.

Note: n.s. means nonsignificant.

table 2. First, the posterior expected parameter values have mostly the expected sign. The probability of a crisis thus tends to increase with the lending boom, mounting debt relative to reserves, the contagion indicator and the deviation of the exchange rate from its trend. In contrast, robust growth, rising market indices and current account surpluses reduce the risk of a currency attack. The only somewhat counterintuitive result, which is consistently confirmed in all estimations, is the positive sign of the government balance variable.[9]

However, the lack of robustness of the relationships under study becomes evident when we consider the posterior inclusion probabilities reported in table 2. Since we assign equal prior probability to all models when computing the posterior model averaged objects, our prior on the inclusion probability of each variable is 0.5.[10] A look at the data shows that the probabilities of including each variable decreases strongly with respect to the prior, with none of the posterior probabilities being higher than 10%. To put it differently, the model with the greatest posterior probability (in fact one that is very close to 1) implies a constant crisis probability that is not country or time specific (i.e., the model including only a constant).

Table 3 is constructed in the same manner as table 2 for the dynamic model and includes lags of the dependent variable. With the exception of the government balance variable, all variables turn out to have the expected signs again, which – if significant – coincide with those obtained in the benchmark study. However, except for the market indices, this time our coefficients appear to be substantially smaller in magnitude than Bussière's (2007). The

[9] *However, it should be borne in mind that the sample for all estimations starts in 1994, and it is a well-known fact that first generation models generally fail to explain crises in the 1990s. This somewhat surprising result might actually support second and third generation models (see for example Krugman, 1996, and Bussière, 2007).*

[10] *There are $2^{\overline{K}-1}$ models including a given variable and $2^{\overline{K}}$ total models, so the prior inclusion probability of a given variable is $2^{\overline{K}-1}/2^{\overline{K}} = 0.5$.*

Table 3

BMA Results – Dynamic Model

Variable	Dynamic		Dynamic uncorrelated		Bussière (2007) dynamic	
	$E(\beta_i \mid Y)$	Inclusion prob.	$E(\beta_i \mid Y)$	Inclusion prob.	Simple dynamic	Fixed effects
Crisis index, lag 1	0.582846	0.003311	0.584356	0.003343	n.s.	n.s.
Crisis index, lag 2	0.034475	0.000722	0.037394	0.000722	n.s.	n.s.
Crisis index, lag 3	0.032963	0.000723	0.036480	0.000723	n.s.	n.s.
Crisis index, lag 4	0.357034	0.001151	0.359204	0.001157	n.s.	n.s.
Crisis index, lag 5	0.776955	0.015559	0.778136	0.015779	[1.636;1.909]	[1.298;1.615]
Crisis index, lag 6	0.760693	0.014288	0.761846	0.014475	[1.344;2.036]	[1.229;2.057]
Exchange rate, deviation from trend	0.007840	0.001315	0.007729	0.001296	[0.037;0.056]	[0.042;0.599]
Lending boom	0.004101	0.002564	0.004100	0.002567	n.s.	n.s.
Short-term debt/reserves	0.000455	0.001331	0.000457	0.001329	[0.003;0.004]	[0.009;0.011]
Total debt/reserves (lc)	0.000252	0.001263			[0.0017]	[0.005]
Total debt/reserves (cc)	0.000332	0.001694			[0.003]	[0.007]
Current account balance	−0.013013	0.001436	−0.013017	0.001437	n.s.	[−0.082]
Government balance	0.020321	0.000945	0.020402	0.000947	n.s.	n.s.
Financial contagion	0.023864	0.011573	0.023900	0.011740	n.s.	[−0.056;0.052]
Datastream index, total market	−0.002978	0.007926	−0.002984	0.008090	n.s.	n.s.
Datastream index, banks	−0.003200	0.022722			[−0.011]	[−0.013]
Datastream index, financial institutions	−0.003408	0.028988	−0.003407	0.029626	[−0.011]	[−0.016]
Growth rate	−0.007056	0.000843	−0.007230	0.000846	n.s.	n.s.

Source: Authors' calculations.

Note: n.s. means nonsignificant.

posterior inclusion probabilities are once more well below the 0.5 threshold. In other words, including six de facto new variables does not improve the explanatory power of macroeconomic fundamentals. Bussière finds that the dependent variable is significant only at lags 5 and 6 in both models, with and without fixed effects. His interpretation of this result is that crises sometimes hit in two waves such that the first attack is often followed by a second bout within a short time interval. In this context, it is also interesting to note that all the coefficients of the lagged crisis index in our and Bussière's regressions enter with a positive sign. Hence, past crises tend to increase the likelihood of repeated attacks, a result which is not quite obvious ex ante. On the one hand, a country that experienced a crisis may be deemed more vulnerable by investors, which would increase the likelihood of a positive sign. On the other hand, however, there are two arguments why crises in the past might reduce the probability of an attack in the future. In the short run, there is not much speculative capital left to be withdrawn after a currency run. In the longer run, one can argue that a country that was already hit by a crisis will have improved its vigilance and supervision mechanisms, which should render another crisis less likely.

In order to account for a general dynamic structure in the model, Bussière (2007) regresses in a standard logit model (without fixed effects) the dependent variable on six chosen explanatory variables

$(REERDEV, LB, STDR, \frac{CA}{GDP}, CONT, GROWTH)$ which are all lagged by

1 to 24 months. This series of regressions thus provides him with 24 different models and 144 different coefficients from which the author draws the conclusion that "some variables have a very short-term impact, such as the

short-term debt to reserve ratio, some have both a very short-term and a longer-term impact (such as the contagion variable), some have a short- to medium-term impact (such as the lending boom), some always seem to have an impact (such as the exchange rate), while for growth and the current account, no impact can be detected" (Bussière, 2007, page 26). We conducted a different exercise at this point and constructed the BMA exercise, using as explanatory variables 6 lags of the crisis variable and 24 lags of all 12 variables listed in table 1, all at the same time. Hence, this setting contains 294 potential explanatory variables, which implies 2^{294} (more than 3×10^{88}) different models over which we have to average. Given the fact that, with the current technology, this does not appear possible in a lifetime,[11] we used the MC^3 approach described above to evaluate the posterior objects.

In table 4 we confine ourselves to reporting only the results for the lags of each variable with the highest posterior inclusion probability.[12] Focusing on the coefficients in the second column, one can note that some of the signs now have changed into an unexpected direction. The government surplus, which used to carry a counterintuitive positive coeffcient now has got the "right" negative sign, while more robust growth, higher current account surpluses and lower lending suddenly and counterintuitively increase the probabiliy of a crisis – at least for the lags with the highest inclusion probability. As if this was not puzzling enough, the sign of the coefficients is not uniform for all lags but rather alternates from positive to negative for all variables. Interestingly enough, the fluctuation pattern looks in many ways very similar to the one derived by Bussière (2007), as can be seen in charts 1–4, which present the parameters estimated by BMA against Bussière's results. In his estimations, e.g. growth only has the expected negative sign for lags 1 to 8 and 16 to 19. Similarly, current account surpluses lagged by more than 11 months increase the probability of a crisis. The latter is also more likely the lower the lending boom was 18 months or more ago. It has to be added, however, that growth, the current account and the lending boom from lag 13 on are not significant.

Among the remaining variables which carry the same sign as in the previous calculations (for the lag with the highest posterior inclusion probability at least), it strikes that the effect of the lagged crisis binary variable is again the most robust at lag 5. In addition, the effect of the exchange rate deviation from trend is now almost 20 times bigger than in tables 2 and 3. This is because the coefficient of the exchange rate variable shows a strong bell-shaped form, rising strongly between lags 4 and 10 and decreasing sharply after that. This contradicts somewhat Bussière's results according to which the exchange rate effect seems much more homogeneous and significant for all lags. It may also be pointed out that all market signals seem to be most symptomatic of tension on the exchange rate market two years before a crisis, which is not quite easy to interpret either.

[11] *If it took only 0.001 seconds to estimate one model, the whole calculation would last $1.009\text{x}10^{78}$ years. Although the reasoning put forward above could also imply that interactions between long- and short-term variables play an important role in unwinding currency crises, due to the extra computational burden imposed by the use of cross-products, we do not embark on this type of exercise in the present study.*

[12] *The complete set of results is available from the authors upon request.*

Table 4

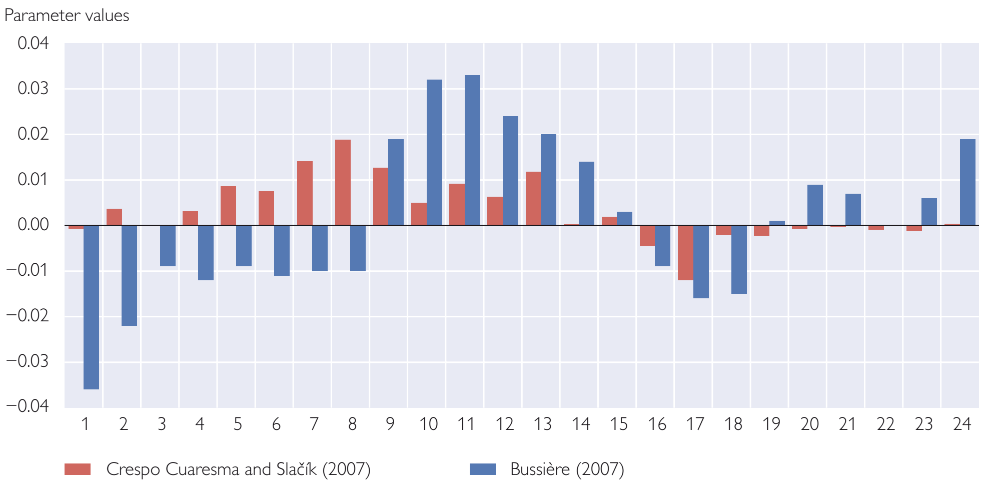
BMA Results: Dynamic Model with Lagged Explanatory Variables

Variable	$E(\beta_i \mid Y)$	Max. inclusion probability	At lag
Crisis index	0.47073	$2.08*10^{-5}$	5
Current account balance	0.023066	$3.18*10^{-5}$	24
Government balance	−0.017251	$1.30*10^{-5}$	18
Growth rate	0.008615	$1.69*10^{-5}$	5
Lending boom	−0.000927	$1.02*10^{-5}$	13
Financial contagion	0.035614	$9.55*10^{-5}$	5
Datastream index, banks	−0.005556	$4.22*10^{-5}$	24
Datastream index, financial institutions	−0.005589	$6.07*10^{-5}$	24
Datastream index, total market	−0.010482	0.000154	24
Exchange rate, deviation from trend	0.129465	0.894149	10
Short-term debt/reserves	0.00066	$1.98*10^{-5}$	7
Total debt/reserves (cc)	0.000435	$3.53*10^{-5}$	23
Total debt/reserves (lc)	0.000183	$1.93*10^{-5}$	22

Source: Authors' calculations.

Chart 1

GDP Growth – Estimated Parameters at Lag Lengths 1 to 24 Estimated

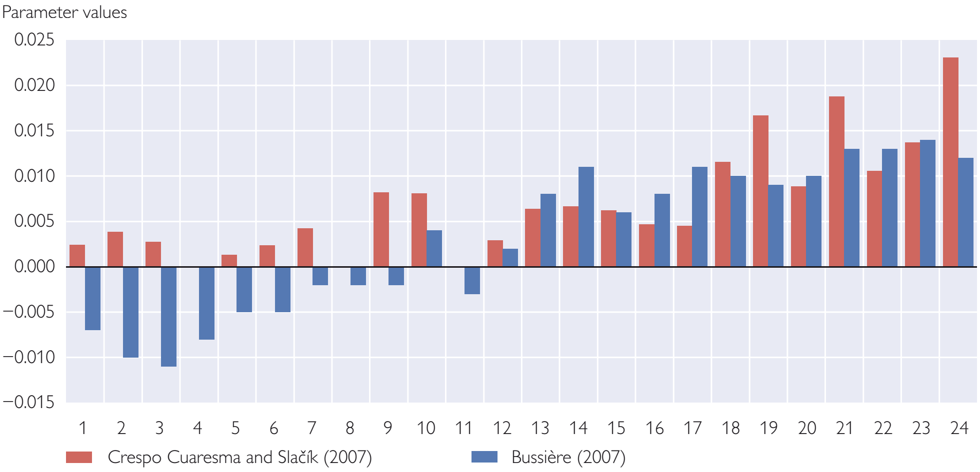


Source: Authors' calculations and Bussière (2007).

As can be seen in the fourth column of table 4, which displays the lag with the maximum posterior inclusion probability for each variable, all values but one are far too small. Only the deviation of the exchange rate from trend at lag 10 shows a posterior inclusion probability above the prior of 0.5. Although the importance of the variable is clear, by no stretch of the imagination can we think of any plausible explanation for the fact that only lag 10 appears robust, and even less so if we consider the fact that the second-highest inclusion probability for this variable (at lag 9) is more than ten times smaller. We thus suggest that it is just a matter of coincidence and that also in this exercise fundamentals have proven to have no systematic and robust explanatory power for currency crises.

Chart 2

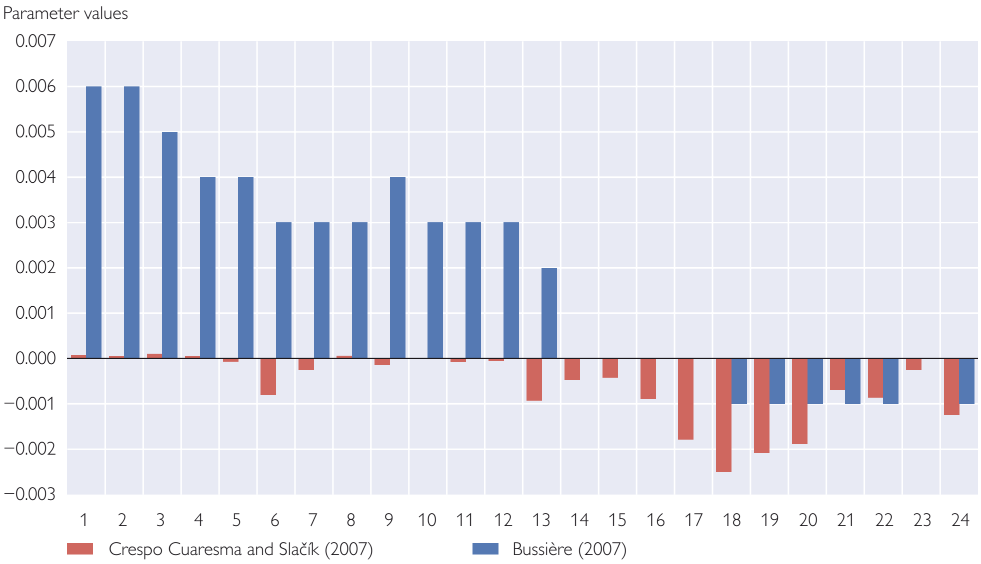
Current Account Surplus/GDP – Estimated Parameters at Lag Lengths 1 to 24



Source: Authors' calculations and Bussière (2007).

Chart 3

Lending Boom – Estimated Parameters at Lag Lengths 1 to 24



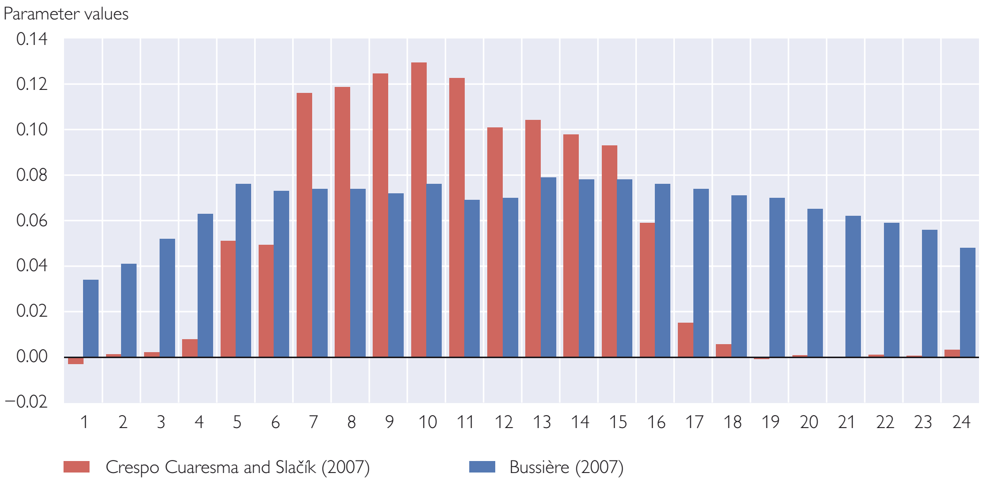
Source: Authors' calculations and Bussière (2007).

5 Conclusions

The dominant majority of early warning mechanisms for currency crises employs some version of fundamental-based binary choice models. To our knowledge, none of the papers on the subject tackles explicitly the issue of model uncertainty in currency crisis models. In the present paper, we do take into account model uncertainty in the framework of a binary choice model. By means of Bayesian model averaging we estimate the coefficients for each variable as weighted averages over the alternative models from the model space, where the weights correspond to the posterior probability of each model. In order to determine the value added by this approach as opposed to

Chart 4

Deviations of the Real Exchange Rate from Trend – Estimated Parameters at Lag Lengths 1 to 24



Source: Authors' calculations and Bussière (2007).

"standard" logit regressions we used the same data set as Bussière (2007), one of the most recent studies on the subject.

If the discrete dependent variable is constructed so as to predict the exact month in which a crisis may happen, our conclusions are twofold. On the one hand, we found that coefficients mostly have the expected signs that also coincide with those of the benchmark study. On the other hand, however, our principal quality gauge – the posterior inclusion probability (i.e. the sum of posterior probabilities of all models containing a particular variable) – unveils a lack of robustness in the relationships between regressors and the dependent variable. These results imply that at least in this setting, the best model to explain a currency crisis is a mere time- and country-unspecific constant. Our results, therefore, indicate that none of the usual macroeconomic fundamental variables is a robust determinant of currency crises for the definition and sample used.

Since our sample starts in 1994, it could well be that the episodes of currency distress included in the sample are crises of the second and third generation type. In this case it would not be surprising that the explanatory power of fundamental data is only limited. To turn the argument around, fundamentals should play a much more significant role in a sample covering the first-generation type of crises. Exactly along these paths we are planning to conduct our future research.

Another way of testing the different theoretical frameworks proposed by the three generations of currency crisis models would be to group variables by theory and compute the joint inclusion probability of these groups of variables. Constructing groups of variables by theory could be handled in the BMA framework by using the proposal by Brock, Durlauf and West (2003), who use a hierarchical prior in order to sort variables into theories or thematic indicators (see also the recent contribution by Doppelhofer and Weeks (2007) for the concept of jointness of determinants in the BMA framework). Although we did not follow their approach in this paper, we propose it as a potentially fruitful research path.

An interesting issue that has not been tackled directly in this contribution and deserves further scrutiny is the possibility of nonlinear effects in the form of interactions among the potential determinants of crises. Developments in some relevant variables may play a role in preparing the ground for imbalances that lead to a currency crisis when triggered by an unsound development in an additional variable. Interaction terms in a BMA setting could be used to assess the importance of this type of effects.

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